YUKUN MA

Vanderbilt University
Department of Economics

yukun.ma@vanderbilt.edu
Phone: +1 (615) 710-7851

EDUCATION

Ph.D. in Economics, **Vanderbilt University** Aug 2018 - May 2024(expected)
M.A. in Economics, **Peking University** Aug 2016 – May 2018
B.A. in Physics, B.A. in Finance, **Nanking University** Aug 2012 – May 2016

RESEARCH

Research Fields

Econometric theory and practice:

- robust inference for clustered data;
- nonparametric and machine-learning methods ;
- high-dimensional data.

Job Market Paper

(1) Identification-robust inference for the LATE with high-dimensional covariates
   - *Present at NY Camp Econometrics XVII program (April 2023), Chinese Economist Society North American Conference (March 2023), 1st CIREQ Interdisciplinary Ph.D. Student Conference on Big Data and Artificial Intelligence (June 2023), Asia Meeting of the Econometric Society (July 2023).*

Publications

(2) Multiway cluster-robust double/debiased machine learning (joint with Harold D.Chiang, Kengo Kato, and Yuya Sasaki)
   - *Accepted at Journal of Business and Economic Statistics, 40 (3), pp. 1046-1056 (2022)*

Working Papers

(3) Dyadic Double/debiased ML for Analyzing determinants of free trade agreements (joint with Harold Chiang, Joel Rodrigue, and Yuya Sasaki)
   - *Present at New York Camp Econometrics XV program (April 2021), Asian Meeting of Econometric Society (June 2021), North American Summer Meeting (June 2021), 73rd European Meeting of the Econometric Society (August 2021), International Association of Applied Econometrics Annual Conference (June 2021), Southern Economics Association 91st Annual Meeting (November 2021), Midwest Economics Association 86th Annual Meeting (October 2022),*

(4) Doubly robust estimator with weak overleap (joint with Pedro Sant'Anna, Yuya Sasaki, and Takuya Ura)

AWARDS AND FELLOWSHIPS

Vanderbilt University Graduate Fellowship 2018 – present

Kirk Dornbush Summer Research Grants, Vanderbilt University 2021
Graduate Fellowship, Peking University 2016 - 2018

PROFESSIONAL ACTIVITIES

Referee: Journal of Econometric Methods, Econometric Reviews
Programming: R (main), Stata, Python, MATLAB

TEACHING EXPERIENCE

Vanderbilt University, Department of Economics

TA for Ph.D. Courses

Statistical Analysis	Fall 2020 (4.88/5)
Microeconometrics.	Spring 2023(5/5)
Econometrics I	Spring 2020 (5/5)

TA for Masters Courses

Statistical Analysis	Fall 2020 (4.67/5)

TA for Undergraduate Courses

Economic Statistics	Fall 2019 (4.33/5)
Principles of Microeconomics	Spring 2020 (4.67/5), Fall 2022(4.50/5)
Economic Statistics; Fall 2021	Spring 2022(5/5), Spring 2023
Econometric Methods	Fall 2021(4.74/5), Spring 2021(4.86/5)

Peking University, Guanghua School of Management

Optimization in Economics and Finance (Ph.D.)	Spring 2017
Macroeconomics & Policy Analysis (MBA)	Spring 2017

Abstracts

Identification-robust inference for the LATE with high-dimensional covariates

(job market paper)

This paper investigates the local average treatment effect (LATE) with high-dimensional covariates, irrespective of the strength of identification. We propose a novel test statistic for the high-dimensional LATE, and demonstrate that our test has uniformly correct asymptotic size. By employing the double/debiased machine learning (DML) method to estimate nuisance parameters, we develop easy-to-implement algorithms for inference and confidence interval calculation of the high-dimensional LATE. Simulations indicate that our test is robust against both weak identification and high-dimensional setting concerning size control and power performance, outperforming other conventional tests. Applying the proposed test to railroad and population data to study the effect of railroad access on urban population growth, we observe shorter length of confidence intervals and smaller point estimates for the railroad access coefficients compared to the conventional tests.

Multiway cluster-robust double/debiased machine learning

(joint with Harold D.Chiang, Kengo Kato, and Yuya Sasaki)

Journal of Business and Economic Statistics

This paper investigates double/debiased machine learning (DML) under multiway clustered sampling environments. We propose a novel multiway cross-fitting algorithm and a multiway DML estimator based on this algorithm. We also develop a multiway cluster robust standard error formula. Simulations indicate that the proposed procedure has favorable finite sample performance. Applying the proposed method to market share data for demand analysis, we obtain larger two-way cluster robust standard errors for the price coefficient than non-robust ones in the demand model.

Dyadic Double/debiased ML for Analyzing determinants of free trade agreements

(joint with Harold Chiang, Joel Rodrigue, and Yuya Sasaki)

This paper presents novel methods and theories for estimation and inference about parameters in econometric models using machine learning for nuisance parameters estimation when data are dyadic. We propose a dyadic cross-fitting method to remove over-fitting biases under arbitrary dyadic dependence. Together with the use of Neyman orthogonal scores, this novel cross-fitting method enables root-consistent estimation and inference robustly against dyadic dependence. We illustrate an application of our general framework to high-dimensional network link formation models. With this method applied to empirical data of international economic networks, we reexamine determinants of free trade agreements (FTA) viewed as links formed in the dyad composed of world economies. We document that standard methods may lead to misleading conclusions for numerous classic determinants of FTA formation due to biased point estimates or standard errors which are too small.

Doubly robust estimator with weak overleap

(joint with Pedro Sant'Anna, Yuya Sasaki, and Takuya Ura)

In this paper, we derive a new class of doubly robust estimators for treatment effect estimands that is also robust against weak covariate overlap. Our proposed estimator relies on trimming observations with extreme propensity scores and uses a bias correction device for trimming bias. Our framework accommodates many research designs, such as unconfoundedness, local treatment effects, and difference-in-differences. Simulation exercises illustrate that our proposed tools indeed have attractive finite sample properties, which are aligned with our theoretical asymptotic results.